2024, Volume 47, Issue 93, 57-88/ ISSN 2304-4306

ECONOMÍA

revistas.pucp.edu.pe/economia

FONDO EDITORIAL

www.fondoeditorial.pucp.edu.pe

Climate Risk Stress Test: Impact of Climate Change on the Peruvian Financial System

Daniel Romero [a], Juan Carlos Salinas [b], Jacqueline Talledo [c]

[a]Research Department of the SBS
✉ dromerov@sbs.gob.pe

[b]Research Department of the SBS
✉ jsalinas@sbs.gob.pe

[c]Research Department of the SBS
✉ jtalledo@sbs.gob.pe

Abstract

We develop the first climate risk Stress Test for the Peruvian financial system following a top-down approach. Focusing on the microeconomic channel, we evaluate how heavy rainfall and droughts, under a scenario of pure physical risk, will marginally affect the probability of default (PD) of borrowers by 2050. Using information from the Credit Registry, the National Oceanic and Atmospheric Administration (NOAA), and CMIP6 precipitation projections (37 modeling groups), we calibrate the marginal impacts differentiating by economic sector and geographical location. We find that, on average, by December 2050, the probability of default of the Peruvian financial system would increase by 4.9% with respect to December 2020. By geographic area, borrowers located on the northern coast (Piura, Lambayeque) and the southern highlands (Ayacucho, Cusco) would be negatively affected by heavy rainfall, while the rainforest (Madre de Dios, Ucayali) would be negatively affected by droughts. Moreover, the economic sectors affected by heavy rainfall or droughts would be agriculture, commerce, and transportation & communications.

Article History: Received: 26 October 2023 / Revised: 30 November 2023 / Accepted: 30 January 2024

Keywords: Climate risk, stress testing, CMIP6, IPCC, heavy rainfall, floods, droughts, credit risk, probability of default, NGFS.

JEL Classification: Q54, Q58, G21, G24, G33, C25

https://doi.org/10.18800/economia.202401.003

1. Introduction

Current changes in the climate system and those expected in the future will increasingly have significant and detrimental impacts on human and natural systems (Ara Begum et al., 2022). Hence, climate action is becoming ever more important, drawing the attention of governments, non-governmental organizations, small and large businesses, and citizens. Climate change, being a global phenomenon, requires a coordinated response at the international level. In this context, the Paris Agreement and the Sustainable Development Goals (SDGs), along with other targets and frameworks, provide much needed overarching goals and policy context.

In the absence of climate policies aimed at curbing greenhouse gas emissions, climate change will lead to an increased frequency and severity of extreme climate events[1] and long-term gradual shifts of global climate[2]. The financial losses and economic costs produced by these changes are known as physical climate risks. In the other end, the introduction of mitigation and adaptation policies entail a different set of challenges, generating what is known as transition climate risks. Physical climate risks can have an impact on financial institutions by disrupting its normal operations or by affecting their counterparties. Transition climate risks arising from climate policies targeting polluting industries can affect those financial institutions most exposed to those sectors. Taken together, it is clear that climate risks might have a significant impact on individual financial institutions and even on the financial system.

Central banks and supervisors around the world are already taking steps to identify, assess and understand how to mitigate climate risks in the financial system (NGFS, 2021). One of the tools to advance these objectives are climate risk stress tests. Standard stress tests tend to focus on the resilience, in terms of solvency, of the financial system to severe but plausible adverse scenarios. Climate stress tests also intend to assess the resilience of the financial system, but under climate trajectories which capture different combinations of physical and transition risks. Against this backdrop, we develop the first climate risk stress test for the Peruvian financial system, drawing on international experience from financial supervisors and international organizations and focusing on physical climate risks derived from extreme precipitation events. The framework, which includes key assumptions, for this climate risk stress test is presented in Section II.

Our climate risk stress test seeks to measure the impact of extreme precipitation events on default probabilities —by region, economic activity, and the Peruvian financial system as a whole— under a scenario in which average global temperature rises by 2.4°C in the medium term[3]. We begin by estimating the historical relationship between extreme precipitation events and district-level probabilities of default segmented by economic sector.

Next, using precipitation projections under a scenario of very high greenhouse gas emissions that focuses on physical risk, we find that the probability of default of the Peruvian financial system would increase —on average— by 4.9% by 2050 with respect to December 2020. Section

[1] For example, heatwaves, floods, landslides, and wildfires.

[2] For example, rising sea levels and changes in precipitation.

[3] Medium term refers to the period 2041-2060 and the increase in temperature is with respect to the average temperature of the 1850-1900 period.

III provides detailed information on data sources and climate scenarios. The empirical strategy is then explained in Section IV, while more detailed results, including decompositions by economic activity and geographical location, are presented in Section V. Finally, conclusions and potential extensions of the current version of this climate risk stress test are outlined in Section VI.

2. Key Concepts, International Experience, and Analytical Framework

2.1 Climate risk

The Basel Committee on Banking Supervision [4] (2020) refers to climate-related financial risks as "the set of potential risks that may result from climate change and that could potentially impact the safety and soundness of individual financial institutions and have broader financial stability implications for the banking system". In turn, this group of risks can be categorized into physical risks and transition risks.

Physical risks are the economic costs and financial losses that result from the increasing severity and frequency of acute physical risks and chronic physical risks. Acute physical risks refer to extreme weather events associated with climate change such as heatwaves, landslides, floods, wildfires, storms, etc. Meanwhile, chronic physical risks include the long-term gradual shifts of the climate, such as changes in precipitation, ocean acidification, rising sea levels, rising average temperatures, etc. In addition, even though physical risks are categorized into two groups, this does not imply that both are independent. For instance, extended periods of increased temperatures may lead to the increased occurrence of wildfires (BCBS, 2021).

Transition risks are the losses related to the adjustment process to a low-carbon economy. These kinds of risks can arise from changes in public sector policies, innovation and shifts in the affordability of existing technologies or movements in consumer and investor sentiments towards a greener environment. With respect to government policies, measures to curb greenhouse gases (GHGs) include energy transition policies, regulations to control pollution, subsidies, taxes, among others. Regarding technological change, the reduction in GHGs emissions may be associated with the development of energy-saving and low-carbon transportation, the increasing use of non-fossil fuels, etc. which, in turn, can disrupt existing business models. Finally, the incorporation of climate risk considerations into the investors' investment decisions and the increased demand for climate-friendly financial products by consumers may require business strategy adjustments of firms and banks, respectively (BCBS, 2021).

2.2 Transmission channels and financial risks

Climate risks can be linked to the financial risks faced by banks and the financial system through a series of transmission channels. The BCBS (2021) classifies transmission channels as microeconomic or macroeconomic. Microeconomic transmission channels include the effect of climate risks on banks themselves —through damage to the financial infrastructure—, on the banks' counterparties —firms and households—, and on its physical or financial assets —e.g. physical

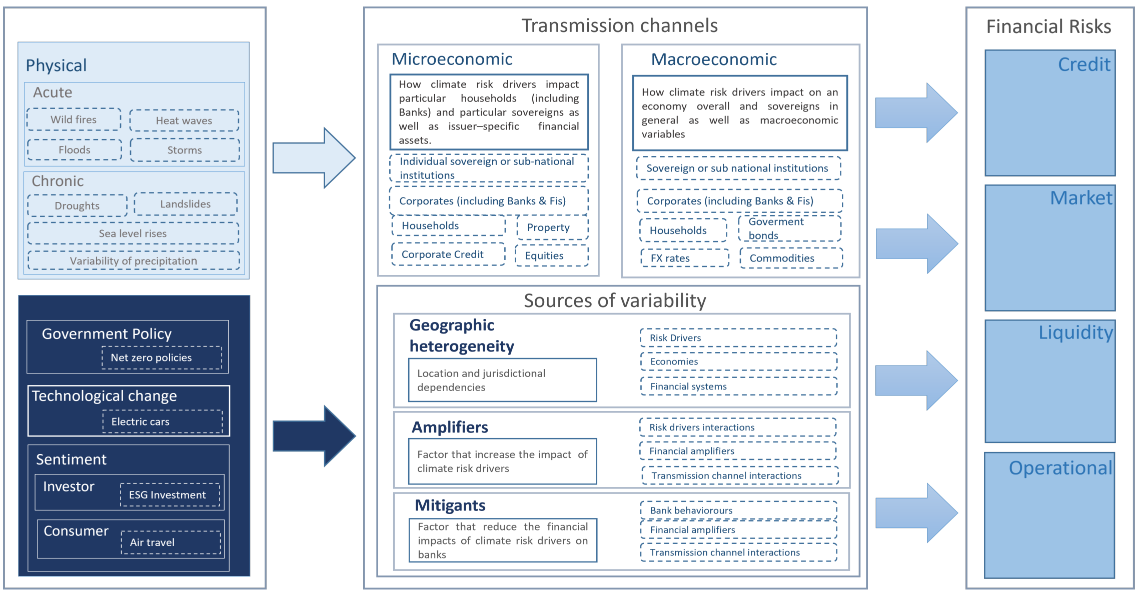
[4] BCBS.

assets such as machinery or realty, or stocks and bonds—. In contrast, macroeconomic transmission channels comprise the mechanisms by which climate risk affects both macroeconomic factors —e.g. economic growth and labor productivity— and macroeconomic market variables —e.g. risk-free interest rates, inflation, and exchange rates—, which, in turn, impact banks.

Both physical and transition risks, through microeconomic and macroeconomic transmission channels, can have an impact on banks through conventional risk categories, namely credit risk, market risk, liquidity risk and operational risk. According to the BCBS (2021), the literature has focused mainly on the impact of climate risk on banks' credit risk and, to a smaller extent, on market risk due to data availability for the calibrations of impacts. With respect to credit risk, events of physical climate risks —like floods— can impact both the ability of a borrower to generate revenues, and thus its ability to repay a loan, and the value of the collateral —e.g. house prices— backing the loan. In other words, climate risk events can lead to higher expected losses for banks through an increased probability of default (PD) and a higher loss given default (LGD).

Climate risk may also impact market risk. The increased occurrence of severe weather events or changes in regulations —by revealing new information about future economic conditions— may lead to a repricing of certain assets, mainly through price reductions, and increased market volatility. In terms of liquidity risk, climate risks may impact the ability of banks to liquidate assets or raise funds as well as increase the demand for liquidity of their customers —whether firms or households—. Finally, in terms of operational risk, physical risk events can damage transportation and telecommunications infrastructure, hampering the regular functioning of banks (BCBS, 2021). A summary of the transmission channels of climate risk variables to the financial sector is shown in Figure 1.

Figure 1. Financial risks from climate risk drivers



Source: Basel Committee on Banking Supervision (2021)

2.3 Climate risk stress tests: International experience

A growing number of central banks and financial supervisors around the world are undertaking exercises designed to identify, assess, and understand the impact of climate risks on their economies and financial systems. Given that these types of exercises are relatively new, each authority has some flexibility to determine the scope, assumptions, or other technical details regarding its exercises (NGFS, 2021).

The Network for Greening the Financial System (NGFS) was established in 2017 —amid an increased awareness of the potential effect of climate change on the financial system— by eight central banks and financial supervisors[5]. Its objective is to strengthen the global response required to meet the goals of the Paris agreement and to enhance the role of the financial system to manage risks and to mobilize capital for green and low-carbon investments (NGFS, 2022). In line with this objective, the NGFS has developed a set of climate scenarios as a common starting point for analyzing climate risks to the economy and financial system. This effort has facilitated the conduction of climate risk stress tests by its members, contributing to the consistency and comparability of results (NGFS, 2020).

According to a report by the NGFS (2021), based on the information provided by 31 of its 121 members, all exercises cover the banking sector —with a particular focus on the impact of climate risks on banks' credit portfolios— and around half of them also cover insurers or other financial institutions. Half of the exercises follow a top-down approach and the other half, a bottom-up approach. Top-down stress tests are performed by the public authority, using its own framework, which includes data, scenarios, assumptions, and models. By contrast, bottom-up stress tests are conducted by individual banks using their own frameworks as part of a system-wide exercise or as part of a stress test where authorities provide common scenarios and assumptions (Baudino et al., 2018).

Regarding assumptions, most of the authorities surveyed consider a 30-year timeframe —in line with the Paris Agreement objective of significantly reducing GHGs by the middle of the century— and a static balance sheet —the portfolios of financial institutions are kept constant throughout the exercise—. Notwithstanding, there are also cases in which the size, composition or risk profile of a bank's balance sheet is allowed to vary over the stress test horizon —that is, a dynamic balance sheet assumption—.

The purpose of this subsection is to gain insights from the climate risk exercises conducted by other institutions around the world. Therefore, we now turn to review in greater detail the experiences of the Bank of England and the European Central Bank - Banking Supervisionn. These central banks have shared a considerable amount of information about their exercises, which makes them particularly useful to define the framework of the climate risk stress test for the Peruvian financial system.

[5]It currently has 121 members.

2.3.1 Bank of England

The Bank of England (BoE) conducted its first exploratory scenario exercise on climate risk, the Climate Biennial Exploratory Scenario (CBES), to assess the capability of the largest UK banks and insurers to quantify and manage their exposure to climate risks (BoE, 2022). The BoE followed a bottom-up approach, in which it provided the participating financial institutions with three scenarios based on the Phase I climate scenarios developed by the Network for Greening the Financial System. (NGFS).

Each scenario is associated with different intensities of both physical and transition risks and would take place over a period of 30 years. Moreover, these scenarios not only consider future climate developments, associated with different sets of climate policies, but also how these interact with the economy. Two scenarios —Early Action (EA) and Late Action (LA)— are mainly concerned with transition risks, whereas the third scenario —No Additional Action (NAA)— centers on physical risk.

Both EA and LA scenarios assume that global warming is limited to an increase of 1.8°C by 2050 relative to pre-industrial levels. The transition to an economy with net zero emissions starts in 2021 in the EA scenario and in 2031 in the LA scenario. The timely adoption of climate policies in the EA scenario leads to a gradual transition with almost no impact on overall GDP growth. By contrast, the initial delay in the LA scenario causes a precipitated adoption of climate policies, which, in turn, generate a short-term macroeconomic disruption with a fall in GDP and a pronounced impact on carbon-intensive sectors.

NAA captures outcomes under the assumption that no additional action is taken to address climate change. A growing concentration of greenhouse gas emissions in the atmosphere lead to global temperature levels 3.3°C higher relative to pre-industrial levels by 2050. This rise in temperature results in chronic changes in precipitation, ecosystems, and sea-levels, along with a rise in the frequency and severity of extreme weather events such as heatwaves, droughts, wildfires, tropical cyclones, and flooding. Both chronic and acute physical risks are coupled with permanently lower UK and global GDP growth and higher macroeconomic uncertainty.

The BoE makes clear that warming levels of 3.3°C by 2050 are not in line with what climate scientists predict under a scenario without the introduction of new climate policies. That particular level of warming —together with its corresponding climate outcomes— is expected between 2050 and 2080 and will lead to global warming of 4.1°C by the end of the century. Then, this decision to bring forward in time higher than expected warming levels allows a better assessment of physical risks without extending the 30-year horizon of the exercise.

As the CBES is a bottom-up climate risk exercise, it includes guidelines for banks and insurers regarding the assessment of the impact of each scenario on their balance sheets. Among other things, the CBES lays out a particular set of transmission mechanisms that should be considered by participating institutions[6]. For example, property exposures —mortgages and commercial real estate— may be affected by price discounts and increased insurance premiums following both coastal and inland flooding. In the case of the largest corporate exposures, the CBES

[6] However, this list is not exhaustive.

requires a counterparty-level analysis which includes possible disruptions of supply chains, the stranding of assets due to the materialization of physical or transition risks, and the direct costs from physical damage.

Bank's loss projections were focused solely on credit risk and assume that balance sheets stay fixed, at their end 2020 values, over the 30-year timeframe. Participant banks quantified the impact of each scenario by portfolio and economic sector in terms of accumulated provisions. Across scenarios, wholesale and mortgage portfolios were the most affected, with significant uncertainty around projected losses.

2.3.2 European Central Bank

The European Central Bank - Banking Supervision (ECB) has completed two climate risk exercises between 2021 and 2022, one with a top-down approach and the other with a bottom-up approach.

2022 climate risk stress test

The European Central Bank - Banking Supervision (ECB), in the context of its Supervisory Review and Evaluation Process, conducted a bottom-up climate risk stress test (CST) whose aim was to understand both the banks' climate risk stress-testing frameworks and their capacity to assess climate risk. In this regard, the CST addressed wider aspects of stress testing and comprised both quantitative and qualitative results.

Participating banks were required to provide data and projections under different climate risk scenarios covering both transition and physical risk as well as short-term and long-term perspectives. For transition risks, the ECB considered a short-term scenario associated with a three-year disorderly transition and three long-term scenarios over a 30-year horizon. The three long-term scenarios —Orderly, Disorderly and Hot House World— have quite similar narratives to the ones used by the BoE and are based on the Phase II NGFS scenarios. The Orderly scenario assumes climate policies are introduced early and gradually become more stringent; the Disorderly scenario considers delays in the implementation of policies; and the Hot House world scenario presumes that no new climate policies are implemented.

The short-term transition scenario assumes a static balance sheet, whereas long-term scenarios allow for changes in banks' exposures to carbon-intensive sectors; that is, a dynamic balance sheet. Additionally, the CST considers the impact of transition risks on credit risk —particularly corporate and mortgage portfolios— and market risk — bonds and stocks issued by non-financial corporations—.

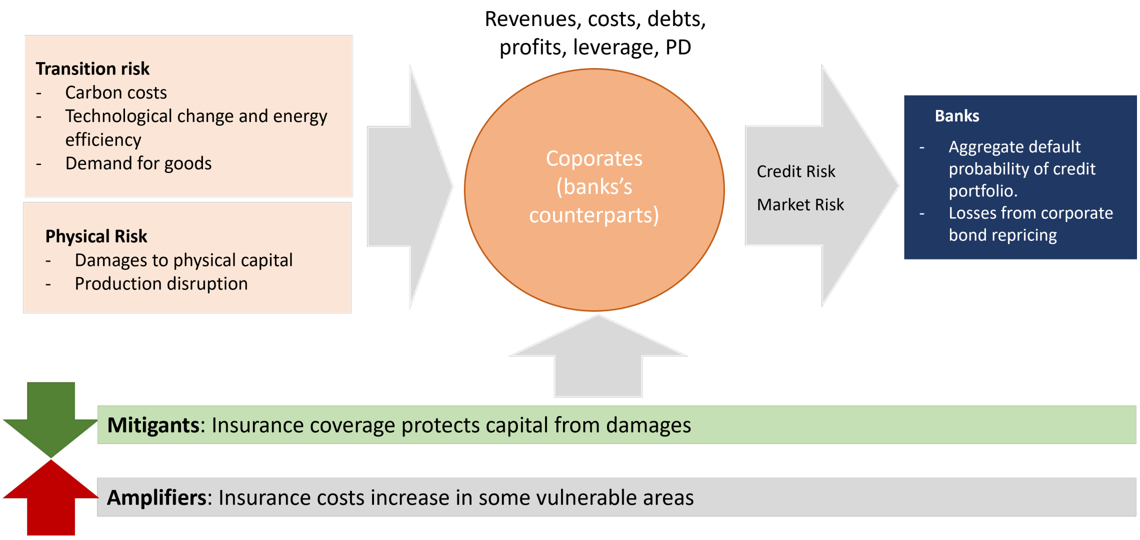
Physical risk scenarios had a different configuration. First, the focus was on two extreme weather events representing key climate risks in Europe: a large flood, a severe drought and heatwave. Second, each acute physical risk was assumed to occur during 2022, which allows banks to use end-of-year balance sheet data. The economic impact of the heatwave is based on NGFS estimates for labor productivity shocks due to heat stress until 2050. The large flood impact is heterogeneous across Europe and follows a risk flood map —which splits regions into four buckets according to their level of flood risk— developed by the ECB. Third, only the effect of physical risks on credit risk was considered. In particular, droughts and heatwaves are assumed to impact banks through their credit exposure to firms, whereas floods impair the value of the underlying collateral of mortgages and credit secured by real estate.

ECB economy-wide climate stress test

Alogoskoufis et al. (2021) describe the ECB's economy-wide climate stress test in detail. This top-down exercise assesses the resilience of non-financial corporations (NFC) and euro area banks to three scenarios with varying levels of transition and physical risks. These scenarios, based on the NGFS Phase I scenarios, follow similar narratives as those previously described. Under the Orderly transition scenario, climate policies are calibrated and implemented in a timely and effective manner leading to limited costs from transition and physical risks. The Disorderly transition scenario assumes a delayed implementation of the required climate policies, which result in significant transition risks and greater physical risks compared to an orderly transition. Lastly, the Hot House World scenario assumes that no policy or regulation is introduced to limit climate change, leading to extremely high physical risks and very limited transition risks.

Scenarios are assumed to take place over the next 30 years to balance the importance of assessing the long-term impact of climate risks with the need to limit the uncertainty around predictions. Moreover, throughout the exercise, the banks' portfolio composition will remain constant, that is, a static-balance sheet assumption is used. The climate stress test quantifies the impact of climate risks on both credit and market risk in two steps. First, the impact of both transition and physical risks[7] on key balance sheet components of non-financial corporations are computed and then translated into firm-level probabilities of default. Second, non-financial corporations default probabilities are translated into credit and market risk impacts on the banking sector (Figure 2).

Figure 2. Schematic overview of climate risk transmission to firms through credit risk



Source: Alogoskoufis et al. (2021)

Specific models were developed to capture the impact of climate risks on non-financial corpo-

[7]In particular, wildfires, floods and sea level rise.

rations. Transition and physical risks affect firm profitability and leverage. Climate policies and technological developments lead to changes in carbon prices and energy costs which will impact firms' operating expenses. Investments to change existing production processes towards greener alternatives will result in higher leverage. In the same vein, extreme weather events damage physical capital, which disrupts the firms' production capacity and revenue generation. At the same time, the replacement of physical capital will require additional investments, which would, again, impact leverage. Insurance premiums and maintenance costs would increase in line with the magnitude and frequency of natural disasters, leading to higher operating costs.

The authors estimate the historical relationship between leverage, profitability, GDP, and inflation[8] with annual probabilities of default using a panel at the firm-year level[9]. Then, projected default probabilities correspond to different levels of the main inputs —namely leverage, profitability, GDP, and inflation— which vary according to the scenario. It is worth noting that changes in profitability and leverage by scenario are also modeled. The estimations rely on a comprehensive dataset which includes both financial and climate information for millions of companies. For example, the dataset includes information on carbon emissions and physical-risk scores —distinguishing between different types of extreme weather events— computed at address level.

The expected loss of banks' corporate loan portfolios is computed for each scenario. The probability of default at the bank level is computed as the weighted average of firm-level default probabilities, where the weight corresponds to the banks' exposure to each individual company. The effect of climate risks on loss given default (LGD) is also modelled, through a microeconomic and macroeconomic channel. The microeconomic channel captures the deterioration of collateral due to physical risk. The macroeconomic channel includes the impact of changes of GDP on LGD. The last component, exposure at default, corresponds to the amount outstanding of each credit in 2020. Additionally, firm-level default probabilities are also used as an input to determine the movements in corporate bonds prices and estimate the market risk impact on banks.

2.4 Analytical framework

In this subsection, we start by presenting some evidence on the impact of extreme precipitation events on individuals and firms to illustrate the microeconomic transmission channel that we are trying to capture. Subsequently, we set up the framework of the climate risk stress test for the Peruvian financial system.

2.4.1 The microeconomic transmission mechanism on credit risk: Impact of heavy rainfall and droughts on the probability of default

Extreme precipitation events can have an impact on the financial system through its effects on individuals and firms. Events such as heavy rainfall or droughts can undermine the ability of debtors to generate revenues or directly reduce their wealth. As a result, borrowers may default

[8]According to the paper, other unspecified macro and firm-level variables are also included in the estimation.
[9]The exact empirical strategy is not mentioned.

on their obligations, leading to a greater share of non-performing loans for financial institutions. Depending on the severity and frequency of the events under consideration, not only individual financial institutions but the financial system as a whole may be affected.

Gutiérrez et al. (2019) provide a clear example of the mechanism described above. They study the effect of heavy rainfall on the financial situation of Peruvian farmers and find that these extreme events, defined at the district level, negatively impact farmers' revenues. As a result, farmers are unable to repay their debts, which leads to a deterioration in their credit risk category.

In another study concerning the agricultural sector, Espinosa-Tasón et al. (2022) study the economic impact of multiyear droughts (2005-2008) in Andalusia. With respect to the impact on producers, they distinguish between rainfed and irrigation farms. Overall, rainfed farms suffer a fall in income, as the drop in production is not compensated by a price increase following the supply contraction. On the contrary, irrigated farms end up with higher incomes due to relatively mild decrease in production which allow them to take advantage of the price increases.

With a focus on firms, Rentschler et al. (2021) explore the impact of floods on busineses in Tanzania. While direct damages can be substantial, they tend to affect a limited fraction of all firms. In contrast, indirect impacts —through infrastructure, supply chains, and workers— are more prevalent and substantial. For example, infrastructure disruptions —regarding electricity and transport— obstruct the operations of firms even when they are not directly located in flood zones. As a result, firms are forced to produce below their capacity.

In a similar fashion as the previous study, Monasterolo (2021) explores the impact of disasters related to heavy rainfall —such as floods and landslides— on supply chains using information from the actual supply chain relations of 1.6 million firms in Japan. Directly damaged firms reduce their production, which, in turn, affect their suppliers and customers, resulting in substantial indirect effects. Using the heavy rainfall events of July 2020, the author finds that daily losses on firms' value-added peaks 50 days after the events.

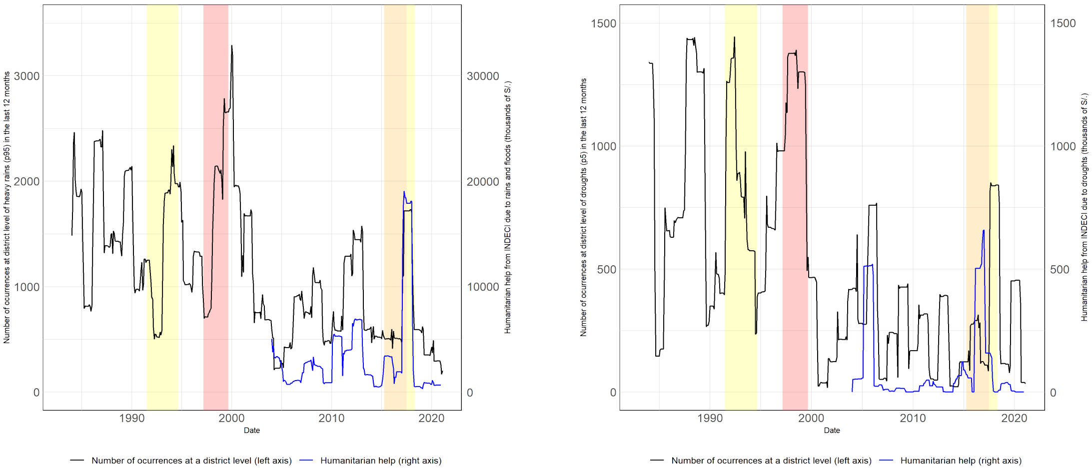
The effect of floods on urban areas can be particularly severe, leading to regional and national impacts. Haddad and Teixeira (2015) estimate the impact of all flooding events in the city of Sao Paulo during 2008. They focus on value chain disruptions due to the temporary closure of businesses around flood points, without taking into account possible disruptions to infrastructure services. The direct impact is heavily concentrated in tertiary activities, especially services, commerce, and transportation. Using a calibrated Spatial Computable General Equilibrium (SCGE) model, the authors find that floods during 2008 in Sao Paulo reduced in 0.026% the GDP of the city and in 0.007% the national GDP.

2.4.2 Climate risk stress test framework for the Peruvian financial system

The climate risk stress test for the Peruvian financial system is built following the international experience and taking into account considerations about data availability. We will use a top-down approach with a 30-year horizon to quantify the impact of physical climate risks on the banking system through the microeconomic transmission channel. In particular, we will focus on the effect of extreme precipitation events —heavy rainfall and droughts— on credit risk.

The focus on heavy rainfall and droughts comes from the fact that both are recurrent phenomena across the national territory. In the past, these events caused significant adverse impacts on people, infrastructure, and economic activity. For example, during the last episode of "El Niño" phenomenon in 2017, more than 1,700 events of abnormal precipitations[10] were registered. As a response to these developments, the National Institute of Civil Defense (Indeci) disbursed a total of S/18 million in humanitarian aid to affected districts (Figure 3).

Figure 3. Heavy rainfall (left) and droughts (right) and humanitarian aid at district level (1983-2020)



Note: Humanitarian aid corresponds to that provided by Indeci in the event of landslides and floods. The colors represent episodes of the El Niño Phenomenon: **Red:** Extraordinary Coastal El Niño Phenomenon. **Orange:** Strong Coastal El Niño. **Yellow:** Moderate Coastal El Niño.
Source: PERSIANN-CCS-CDR, Ministerio de Ambiente, NOAA, Indeci.

Extreme precipitation events can have adverse impacts on firms and households by, for example, restricting their ability to operate or work. Firms experience a fall in revenue and households a fall in income. As a result, both firms and households experience troubles to repay their debts, leading to a surge in the number defaults and, eventually, an increase in non-performing loans in the banking system. It is important to note that extreme precipitation events can also have aggregate impacts on the economy. However, these macroeconomic effects are not included in this exercise.

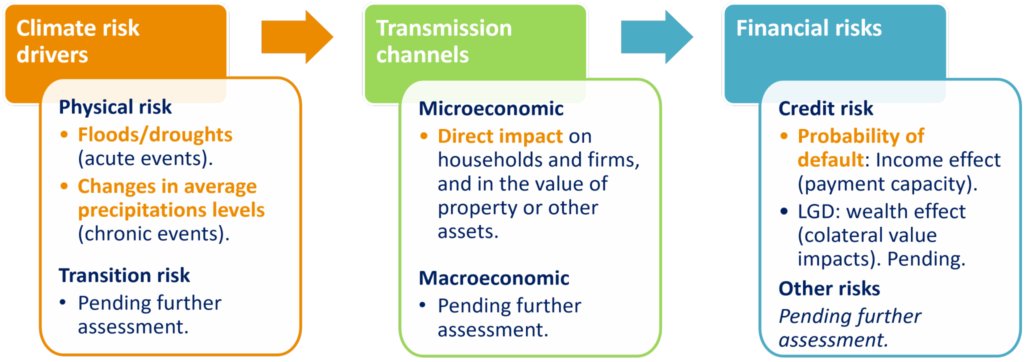
Instead of three scenarios, as in the exercises reviewed before, this climate risk stress test will only have one scenario that will represent a future without the adoption of new climate policies and pronounced climate warming. Therefore, the scenario under consideration will be one of pure physical risk. In terms of the exercises developed by the BoE and the ECB, our scenario is akin to the No Additional Action or the Hot House World scenarios. Further details about the scenario are provided in Section III.

This climate risk stress test will quantify the impact on the banking system —in terms of probabilities of default— of the precipitation levels projected for 2050 under a pure physical risk

[10]Defined as precipitations above the 95th percentile of rainfall distribution over the last 40 years.

scenario. To facilitate the analysis, we assume that balance sheets of financial institutions stay at their end 2020 levels and that no other factor, except for precipitations, change during the 30-year time horizon. Figure 4 outlines the framework of the first climate risk stress test for the Peruvian financial system.

Figure 4. Framework of the first climate risk stress test for the Peruvian financial system



Source: Own elaboration.

3. Data and Climate Scenarios

3.1 Precipitations

There are a number of different precipitation datasets which differ in their spatial resolution, temporal resolution and timespan. Most of the available precipitation datasets provide either high spatial resolution with short-term timespans or low spatial resolution with long-term periods. Against this backdrop, the Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Cloud Classification System-Climate Data Record (PERSIANN-CCS-CDR) database was designed to address these limitations. This dataset, compiled by the National Oceanic and Atmospheric Administration (NOAA), is characterized for being highly granular, providing precipitation estimates with 3-hour intervals since January 1983 at a global scale in areas of approximately $4km^2$ (0.04° x 0.04°). Moreover, when confronted with other datasets, such as the PERSIANN-CDR[11], it shows a better performance in representing the spatial resolution, temporal resolution, magnitude, and spatial distribution patterns of precipitation, especially for extreme events (Sadeghi et al., 2021).

The PERSIANN-CCS-CDR dataset, given its characteristics, is used to determine the monthly precipitation levels by district. Moreover, this dataset is also used to compute the historical distribution of precipitations by district and its associated percentiles, which are needed to identify episodes of heavy rainfall and droughts. There is another source with a substantially larger temporal coverage, the Global Precipitation Climatology Centre (GPCC) dataset. However, the way in which it collects information about precipitations —through rain gauges— poses several

[11] Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record.

limitations. For example, the global number of rain gauges is limited, restricting its overall coverage. Moreover, the distribution of rain gauges around the world is uneven. As a result, in order to cover land worldwide, individual observations are interpolated, a process which smooths extreme values and affects long-term trends (Taylor et al., 2018). For this reason, the GPCC dataset is not used to compute historical precipitation distributions.

3.2 Probability of default

The information used to compute default probabilities comes from the Credit Bureau Data Report named Reporte Crediticio de Deudores (RCD) of the Financial Regulator that monitors financial stability risks in Peru, named Superintendencia de Banca, Seguros y Administradoras Privadas de Fondos de Pensiones del Perú (SBS). Among other variables, it includes monthly information of outstanding debts and days past due by borrower, economic sector, geographical location, credit type[12] and financial institution.

Historical probabilities of default are constructed as the proportion of debt that migrated from non-default to default during a 12-month time frame, where default is defined as 90 days past due. These computations are done for each district and further divided by economic activity for business loans and by credit type for household loans —mortgages and consumer loans—.

3.3 Scenario configuration

Consistent with the objective of this climate risk stress test, we employ the precipitation levels that would be observed by 2050 under a pure physical risk scenario. In this subsection, we provide more details about the configuration of this scenario, including the narrative behind it.

3.3.1 CMIP6

The Coupled Model Intercomparison Project (CMIP) predicts the trajectories of various climate variables under different scenarios that assume particular trajectories for pollution levels and exploitation of fossil-fuel resources at a global scale. Founded in 1995 by the Working Group on Coupled Models (WGCM) of the World Climate Research Program (WCRP), the CMIP is currently the main source of information for the Intergovernmental Panel on Climate Change (IPCC), a United Nations (UN) agency.

The Coupled Model Intercomparison Project Phase 6 (CMIP6) is the most recent gathering of climate modelling institutions around the world. Modeling groups from France, Japan, Germany, Italy, England, Norway, Sweden, Netherlands, Ireland, Spain, Finland, Denmark, Portugal, Greece, Belgium, South Korea, and India have produced close to 100 different climate models. Each institution builds and improves its own climate model to replicate global climatic processes and, every five to seven years, all these institutions gather to use the latest versions of their climate models in a coordinated set of model simulations. This model intercomparison allows the climate science community to assess the performance of the models against earlier

[12] Wholesale business loans, retail business loans, mortgages, and consumer loans (both revolving and non-revolving credit).

versions and also against newly developed models. As a result, scientists can obtain more robust projections, compared to what would be obtained by each climate institution independently, and get a better estimation of the uncertainty around those projections (Government of Canada, 2022).

The CMIP6 serves as the main source of information for the IPCC's Sixth Assessment Report (AR6) prepared in 2022, which focuses on analyzing (i) the impact of humanity on climate variables under different paths of greenhouse gas emission, (ii) the capacity of both humankind and the planet to adapt to climate change, and (iii) the progress in emissions' reduction and climate change mitigation efforts. This last item also includes an assessment of the consistency between national climate commitments and long-term global emissions targets.

CMIP6 scenarios result from the combination of Shared Socio-economic Pathways (SPPs) and Representative Concentration Pathways (RCPs). The SSPs represent alternative narratives about how the world might develop over the coming century in the absence of climate policy (Table 1). Moreover, each SSP includes a set of assumptions about population, urbanization, gross domestic product (GDP), economic growth, rate of technological developments, greenhouse gas (GHG) and aerosol emissions, land-use changes, etc. (Government of Canada, 2022).

RCPs describe the concentration of greenhouse gases (GHG) in the atmosphere over time and correspond to different levels of simulated total radiative forcing by 2100. Radiative forcing is the change in the difference between incoming solar radiation from the sun, and outgoing energy radiated back into space by Earth. By convention, a positive radiative forcing means more energy is retained within the climate system, leading to climate warming. Higher levels of radiative forcing are explained by higher levels of GHG emissions, particularly CO2 emissions. The CMIP6 considers seven different RCPs, ranging from 1.9 to 8.5 W/m^2 (watts per square meter), where higher values correspond to stronger climate warming effects. (Government of Canada, 2021). Figure 5 shows CO2 emissions trajectories under each of the SSP baseline scenarios.

The most adverse scenario in the CMIP6 is $SSP_5 - 8._5$. In this scenario, a trajectory of fossil-fuel development (SSP_5) is coupled with an RCP of 8.5 W/m^2, the highest possible value. The limited or nonexistent global mitigation efforts in this scenario imply low transition risks. At the same time, the absence of climate policies leads to greater concentrations of greenhouse gas emissions which would, in turn, intensify physical risks. As a result, being a scenario of primarily intense physical risks makes it the more appropriate for the present climate risk stress test.

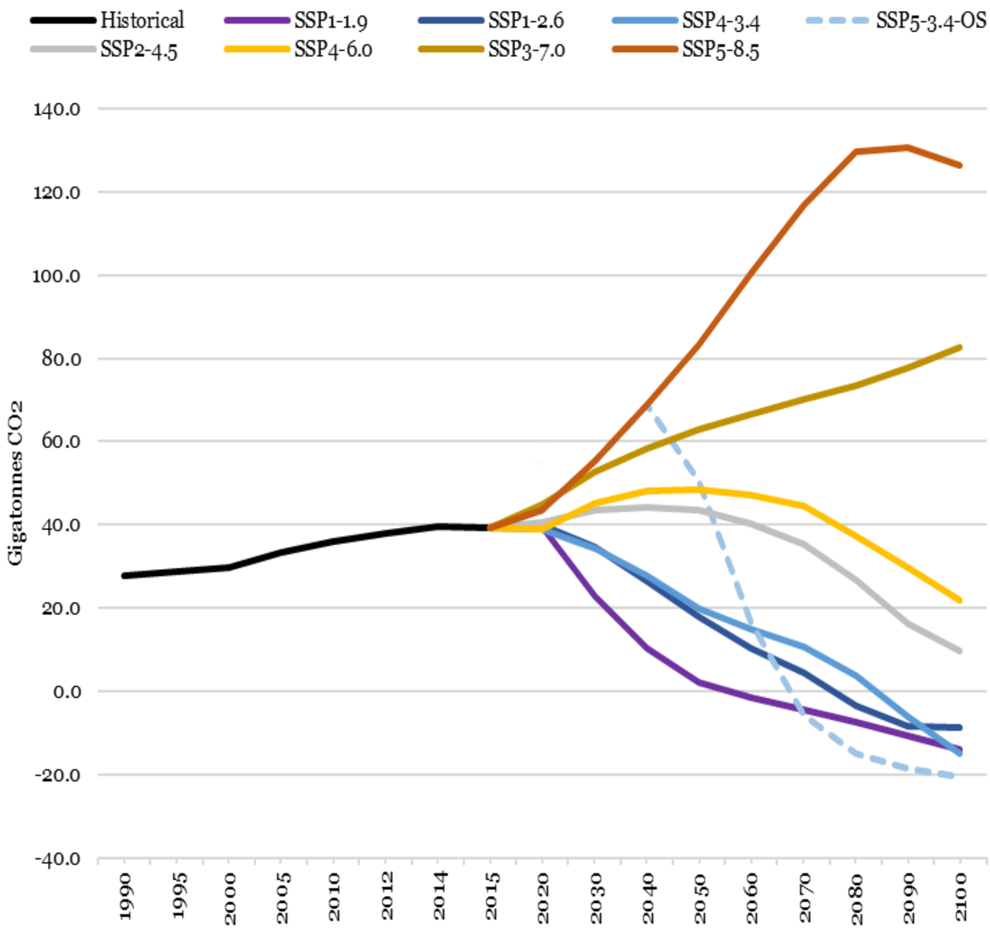
Table 1

Overview of SPP scenarios

Shared Socio-economic Pathway	**Summary of narrative**
SSP1	Sustainability - Taking the green road (low challenges to mitigation and adaptation) • The world shifts gradually, but pervasively, toward a more sustainable path, emphasizing more inclusive development that respects perceived environmental boundaries.
SSP2	Middle of the road - (medium challenges to mitigation and adaptation) • The world follows a path in which social, economic, and technological trends do not shift markedly from historical patterns. • Global and national institutions work toward but make slow progress in achieving sustainable development goals. • Environmental systems experience degradation, although there are some improvements and overall, the intensity of resource and energy use declines.
SSP3	Regional rivalry - A rocky road (high challenges to mitigation and adaptation) • A resurgent nationalism, concerns about competitiveness and security, and regional conflicts push countries to increasingly focus on domestic or, at most, regional issues. • A low international priority for addressing environmental concerns leads to strong environmental degradation in some regions.
SSP4	Inequality - A road divided (low challenges to mitigation, high challenges to adaptation) • Highly unequal investments in human capital, combined with increasing disparities in economic opportunity and political power, lead to increasing inequalities and stratification both across and within countries. • The globally connected energy sector diversifies, with investments in both carbon-intensive fuels like coal and unconventional oil, but also low-carbon energy sources. Environmental policies focus on local issues around middle- and high-income areas.
SSP5	Fossil-fueled development - Taking the highway (high challenges to mitigation, low challenges to adaptation) • This world places increasing faith in competitive markets, innovation, and participatory societies to produce rapid technological progress and development of human capital as the path to sustainable development. • The push for economic and social development is coupled with the exploitation of abundant fossil fuel resources and the adoption of resource and energy intensive lifestyles around the world.

Source: Government of Canada (2021)

Figure 5. CO2 emissions by CMIP6 scenario



Source: SSP database.

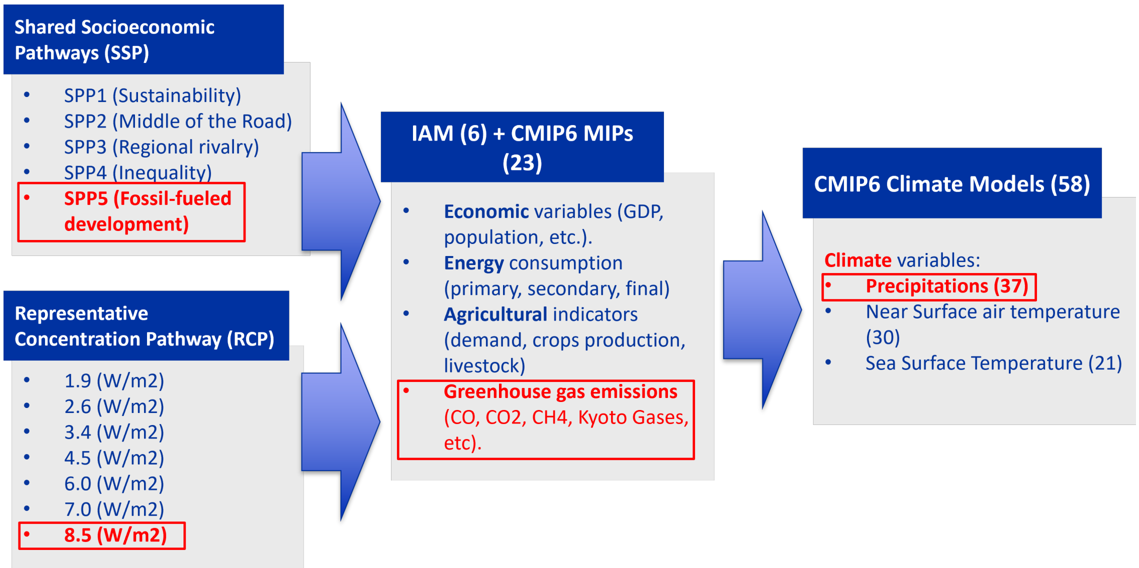
3.3.2 Projections

Over time, the increased scale of each gathering, in terms of models and climate institutions, led to the organization of several Model Intercomparison Projects (MIPs) inside the CMIP, which serves as an integrated framework. MIPs are sets of experiments and simulations designed to test and compare specific aspects of climate models (Government of Canada, 2022). Starting from individual MIPs, future climate change simulations are coordinated within the Scenario Model Intercomparison Project (ScenarioMIP), which is the primary activity within CMIP6 that provides multi-model climate projections based on alternative scenarios of future emissions and land use changes produced with integrated assessment models (IAMs) (O'Neill et al., 2016)

IAMs combine detailed models of energy system technologies with simplified economic and climate science models to evaluate different population, economic and technological pathways, allowing an assessment of the feasibility of achieving specific climate change mitigation goals (Hare et al., 2018). To predict greenhouse gases (CO, CO2, CH4, Kyoto Gases, etc.), IAMs take as inputs socioeconomic variables[13] (GDP, population), energy usage, agricultural and technological indicators and employ general (or partial) equilibrium models with recursive dynamic solutions or intertemporal optimization.

GHGs forecasts resulting from IAM models are harmonized and spatially georeferenced using the MIP models to ensure comparability as part of the effort by the CMIP6 to standardize results. Standardized GHGs forecast will serve as inputs for the 58 different CMIP6 modeling groups to project climate variables (Figure 6). 37 groups project monthly precipitations up to the year 2100 with a spatial resolution of 1.00° x 1.00°[14]. It is worth noting that these projections include both chronic and acute physical risks associated with precipitations; that is, it covers changes in the average rainfall level and extreme events —such as those associated with "El Niño" Phenomena—.

Figure 6. CMIP6: Scenario development (ScenarioMIP)



Source: The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6.

4. Empirical Strategy

The econometric specification relies on monthly panel data where districts are the units of analysis. Hence, we use the following linear panel data model, where "i" denotes the district and "t" the month:

$$y_{i,t} = \alpha_i + \gamma_t + \beta \sum_{h=1}^{12} D^n_{i,t-h} + \varepsilon_{i,t} \tag{1}$$

The dependent variable $y_{i,t}$ is not directly the probability of default, since that would require a logit or probit model. Instead, we use a logarithmic transformation of the probability of default:

[13] As an example, Appendix 2 shows forecasted average annual GDP growth for the World, Latin America, and Caribbean (LAC), and Peru under different SSP scenarios.

[14] See Appendix 2 for detailed information of each modelling group.

$$y_{i,t} = \ln\left(\frac{PD_{i,t}}{1 - PD_{i,t}}\right) \tag{2}$$

In addition, α_i is a district fixed effect that captures time-invariant district characteristics that may affect default probabilities, and γ_t is a time fixed effect that captures time dependent factors that do not vary across districts that may affect default probabilities.

Each $D^n_{i,t}$ is a dummy variable that is defined according to the event that we are trying to capture. For heavy rainfall, the dummy variable activates according to the following rule, where X_i denotes the historical rainfall distribution of district "i":

$$D^n_{i,t} = \begin{cases} 1 & \text{if } X_{i,t} > \text{Percentile}_n(X_i) \\ 0 & \text{if } X_{i,t} \leq \text{Percentile}_n(X_i) \end{cases} \tag{3}$$

Thus, $D^n_{i,t}$ is equal to one if the precipitation level at time "t" for district "i" is greater than the nth percentile of the historical rainfall distribution of district "i" , where $n \in \{80, ..., 99\}$.

Similarly, the dummy variable for droughts activates according to:

$$D^n_{i,t} = \begin{cases} 1 & \text{if } X_{i,t} < \text{Percentile}_n(X_i) \\ 0 & \text{if } X_{i,t} \geq \text{Percentile}_n(X_i) \end{cases} \tag{4}$$

That is, $D^n_{i,t}$ is equal to one if the precipitation level at time "t" for district "i" is lower than the nth percentile of the historical rainfall distribution for district "i" , where $n \in \{1, ..., 20\}$.

Each dummy variable is defined at a district level, since there is considerable heterogeneity in precipitations across the country. For example, 9% of the national territory exhibits an arid type climate characterized by low levels of humidity and annual precipitation levels between 0-700 mm[15]. In clear contrast, 26% of the national area exhibits a climate with a lot of rain and humidity, with annual rainfall between 2100 and 5000 mm (SENAMHI, 2020). As a result, what counts as heavy rainfall or a drought strongly depends on the district under analysis. Figure 7 shows the historical distribution of precipitations for the districts with the lowest and highest precipitation level, respectively.

The parameter β measures the marginal impact of extreme precipitation events —occurring in the last 12 months— on district level default probabilities. The number of lags of the dummy variable included in the model is associated with the definition of default employed, which considers a 12-month timeframe. Given that extreme precipitations events are not correlated with other potential explanatory variables of default probabilities[16], there is no need to include additional control variables to get a consistent estimate of β.

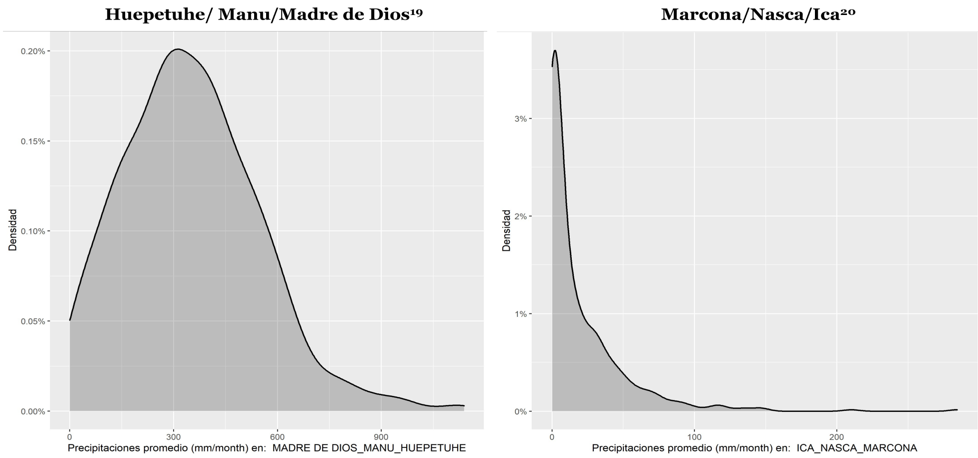
The estimation of β is done separately for each economic activity, plus mortgage and consumer loans[17], and each of the 40 different thresholds which define an extreme precipitation event. The

[15]Precipitation in measured in millimeters, where one millimeter of rain corresponds to 1 liter per square meter of water on the surface.

[16]For example, financial institution characteristics or macroeconomic factors.

[17]In total, we have 17 economic sectors plus mortgage and consumer loans.

Figure 7. Monthly average precipitations (mm): 1983-2020



Source: PERSIANN-CCS-CDR, own calculations.

historical distribution of precipitations for each district are determined using the PERSIANN-CCS-CDR dataset from 1983 to 2020. Default probabilities are computed from January 2001 to December 2019.

5. Results

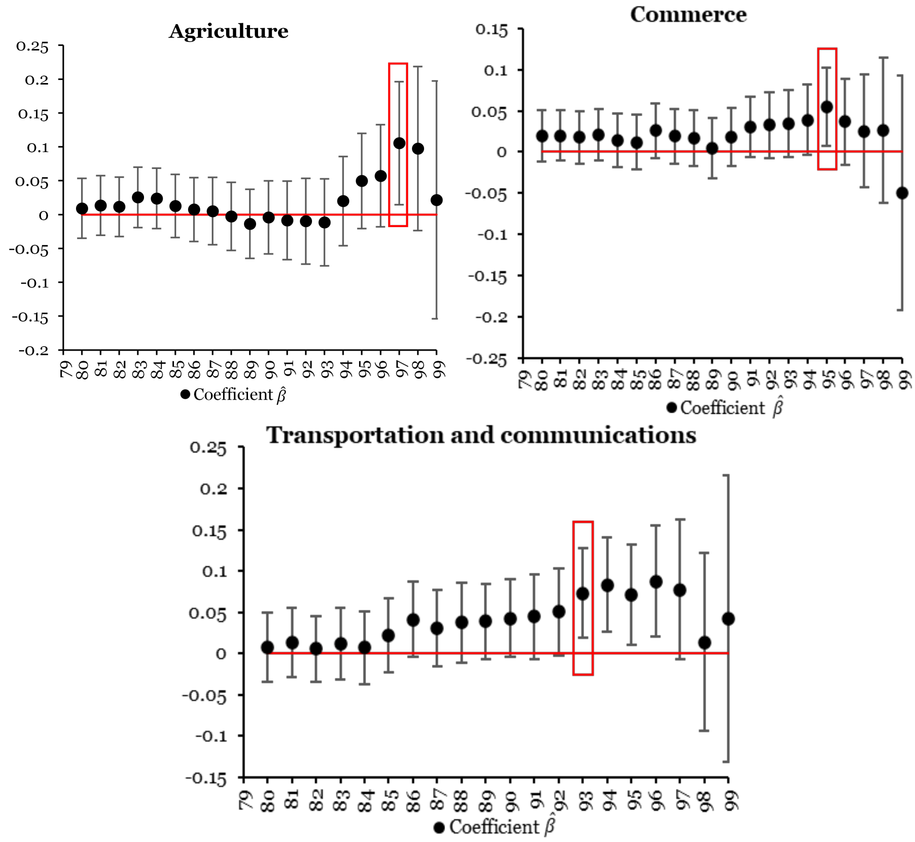
5.1 Historical relationship between default probabilities and extreme precipitation events

Figures 8 and 9 summarize the estimated parameters β —per threshold and for some economic activities— for droughts and heavy rainfall, respectively. The selected economic activities correspond to those for which we find a positive and statistically significant marginal effect of extreme precipitation events on probabilities of default.

The default probabilities of agricultural sector loans rise due to both droughts and heavy rainfall. In particular, precipitation events corresponding to the 1th and 97th percentiles of the historical distribution of precipitations lead to a higher probability of default. Moreover, the effect of droughts is greater in magnitude than the impact of heavy rainfall.

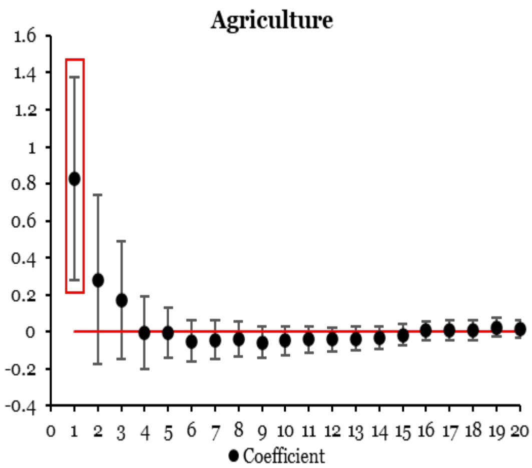
Droughts do not have a positive and statistically significant effect on default probabilities for any other sector, whereas heavy rainfall affects loans in both commerce and transportation and communications. For commerce, rainfall corresponding to the 95th percentile of historical district-level precipitations increases default probabilities. For transportation and communications, the thresholds that lead to a greater default probability are those based on the following percentiles: 93th, 94th, 95th and 96th. In this case, the first significant percentile (93th) was selected, in order to obtain the largest significant affected group.

Figure 8. Impact of heavy rainfall on district-level probabilities of default



Source: : RCD, PERSIANN-CCS-CDR.

Figure 9. Impact of droughts on district-level probabilities of default



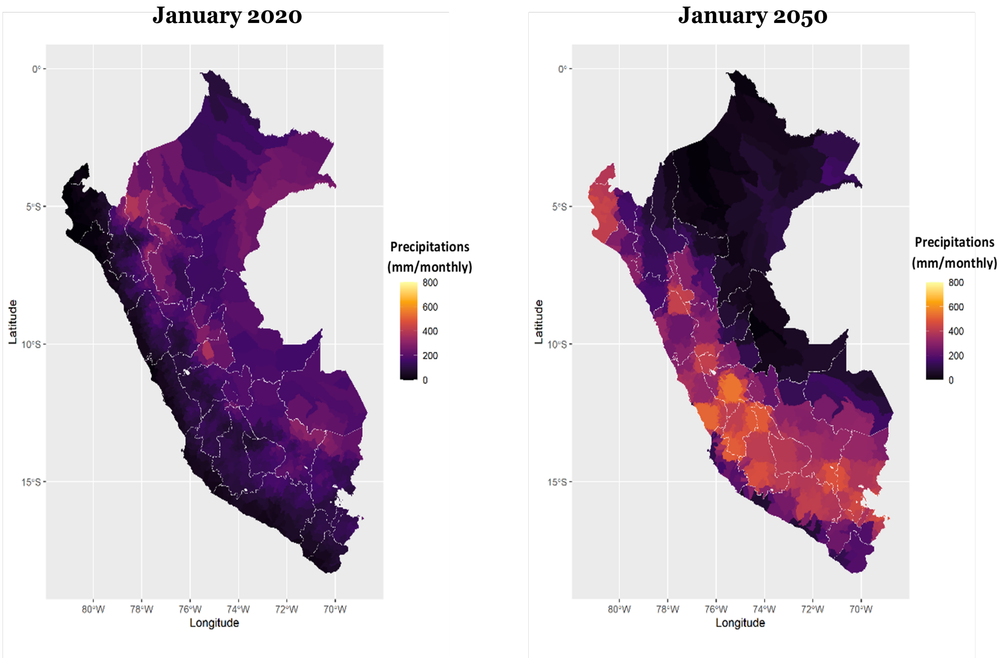
Source: : RCD, PERSIANN-CCS-CDR.

5.2 Potential impact of projected precipitation on default probabilities by 2050

This climate stress test uses a scenario in which the world follows a path of fossil-fueled development. Under this scenario ($SSP_5 - 8.5$ or fossil-fueled economy of CMIP6), global surface temperature will rise about 2.4°C above pre-industrial levels by the year 2050. This is consistent with limited or nonexistent global mitigation efforts and the intensification of physical risks.

Under $SSP_5 - 8._5$, rainfall in the different regions of the national territory would intensify significantly by 2050, with the most affected regions being those located on the northern coast (Piura and Tumbes) and the southern highlands of Peru (Junín, Huancavelica, Ayacucho, Apurimac, Cusco, and Puno). For example, the CAMS-CSM1-0 model predicts that in Piura, rain levels registered in January 2050 in the different districts of the region would be, on average, 15 times stronger than those registered in January 2020 (Figure 10).

Figure 10. Peru: Projected precipitations at the national level (mm per month)



Source: : PERSIANN-CCS-CDR, own calculations.

The estimated parameters β, coupled with precipitations projected by 2050 under the scenario $SSP_5 - 8._5$ by the aforementioned modelling groups, allow us to quantify the marginal impact of climate risk on the financial system's credit risk. The following analysis focuses on agriculture, commerce, and transportation and communications sectors, as these are the only economic activities for which extreme precipitations events have a statistically significant marginal impact.

The proposed linear panel data model has as a dependent variable a transformation of the probability of default. Hence, we apply the following formula to compute the marginal impact of extreme precipitations events on the default probability of district "i" in month "t":

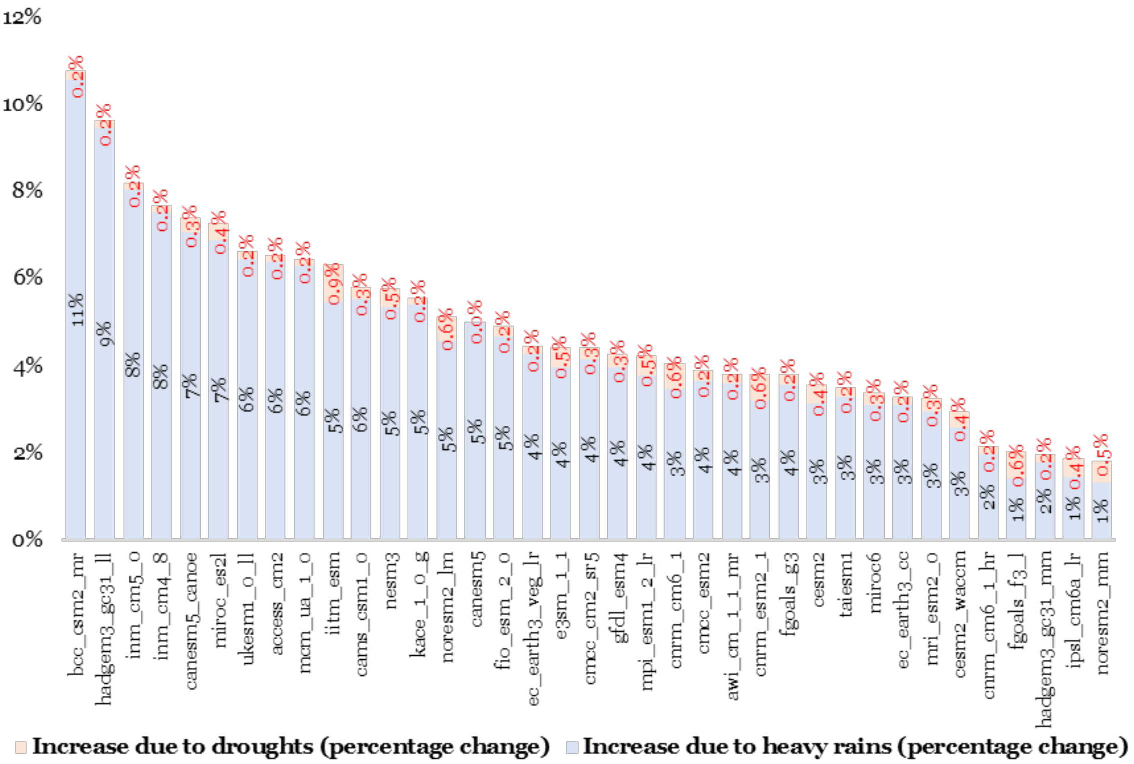
$$\mathrm{PD}_{i,t}^{\mathrm{Stressed}} = \mathrm{PD}_{i,t}^{\mathrm{Baseline}} + \hat{\beta}(\mathrm{PD}_{i,t}^{\mathrm{Baseline}})(1 - \mathrm{PD}_{i,t}^{\mathrm{Baseline}}) \tag{5}$$

As can be seen, the marginal impact on each district depends on its initial probability of default ($PD_{i,t}^{Baseline}$). All results in this section are computed by considering December 2020 probabilities of default as baselines.

As stated in Section III, the CMIP6 has 37 modeling groups which project precipitations. Hence, although we are restricting our analysis to scenario $SSP_5 - 8._5$, we still have 37 different projections for precipitations by 2050. We compute the marginal impact of each projection on default probabilities by region, economic activity, and the financial system as a whole.

On average, by 2050, the probability of default of the Peruvian financial system as a whole would increase by 4.9% with respect to December 2020 due to heavy rainfall and droughts. Depending on the model, the estimated impact ranges from 1.8% to 11.2%, reflecting the uncertainty around climate projections. Figure 11 consolidates the aggregate marginal impact of extreme precipitation events, by model, on the financial system. As can be noted, the bulk of the marginal impact corresponds to heavy rainfall.

Figure 11. Marginal impact of heavy rainfall and droughts on the probability of default of the Financial System by CMIP6 model (%)

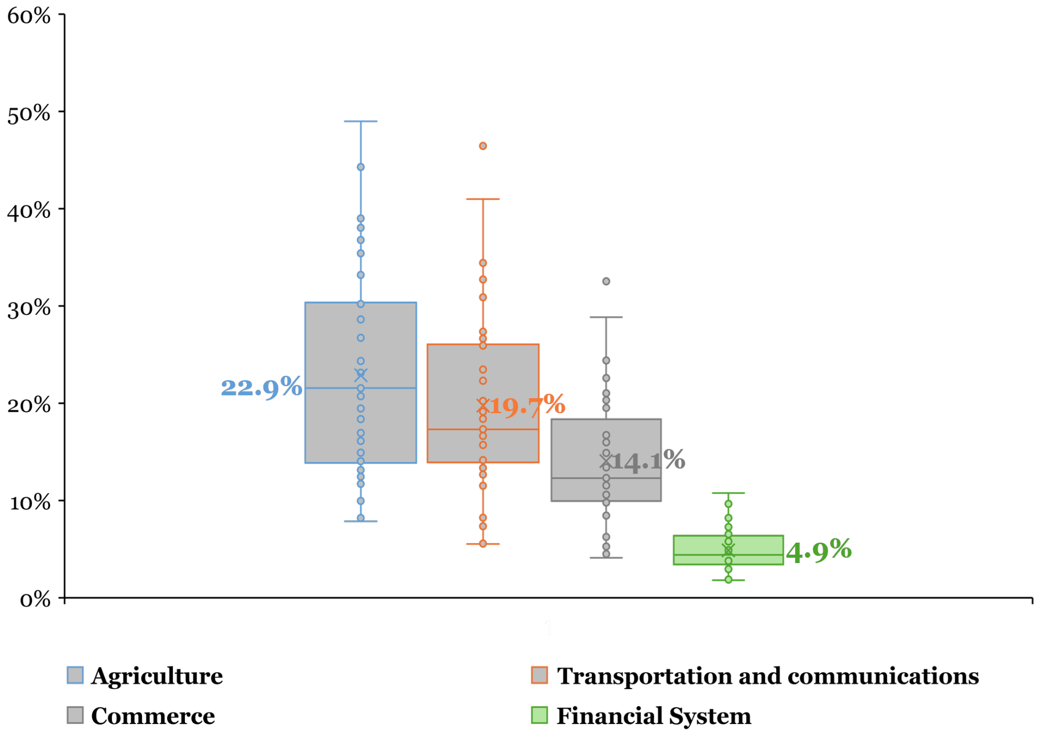


Source: RCD, NOAA, CMIP6.

As shown before, the sectors affected by precipitation events are agriculture, transportation and communications, and commerce. The results indicate that the average percentage increase on default probabilities by economic activity is 22.9% for agriculture, 19.7% for transportation and communications, and 14.1% for commerce. Once again, there is considerable variability around these averages. Agriculture may experience an increase in its probability of default of up to 49%, transportation and communications, 46%, and commerce, 33% (Figure 12).

The calculated marginal impacts come from a district-level estimation; therefore, we can

Figure 12. Marginal impact of extreme precipitations events on the probability of default of the Financial System by economic activity (%)



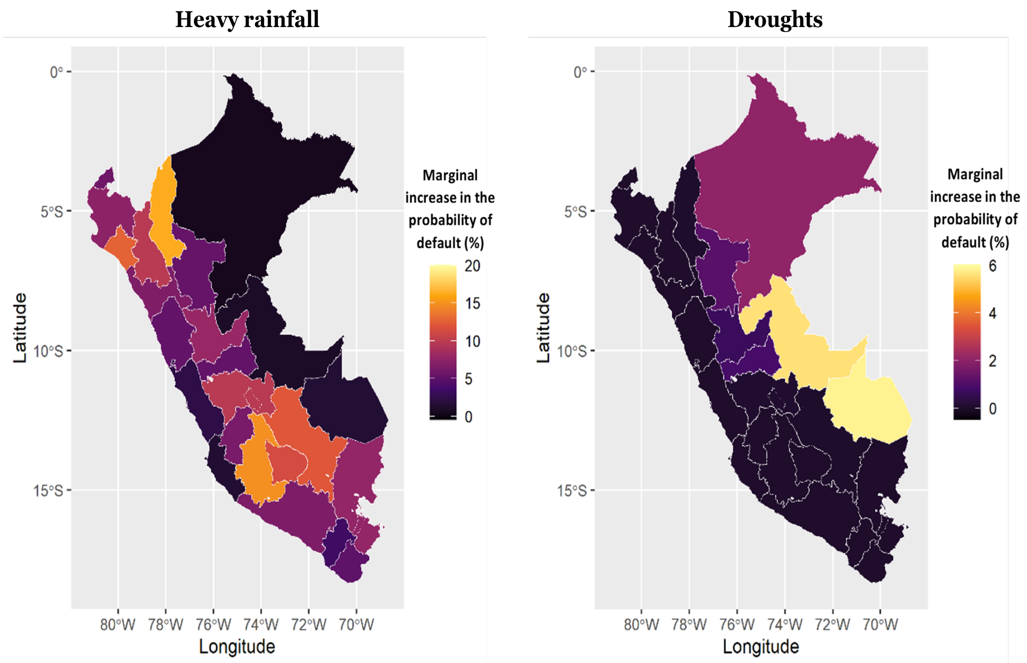
Source: Credit Bureau Data Report, NOAA, CMIP6.

Notes: The box plot summarizes the impact, by economic activity, of each of the 37 precipitation projections under scenario $SSP_5 - 8._5$

also compute results by geographical area. Looking at the impacts by region[18], Amazonas (+16.2%), Ayacucho (+14.8%) and Lambayeque (+12.6%) would exhibit the greatest average marginal increases in default probabilities by 2050. These results are driven by heavy rainfall, with droughts having a much more limited impact. At the other end, default probabilities in Ica (+1.4%), Callao (+1.8%) and Lima (+2.3%) would experience the lowest rises in default probabilities (Figure 13). Results by region and economic activity can be found on Appendix 3.

[18] Each region is divided into provinces and each province comprises several districts.

Figure 13. Marginal impact of extreme precipitations events on the probability of default of the Financial System by region (%)



Source: Credit Bureau Data Report, NOAA, CMIP6, Ministerio de Ambiente.
Impact of the average 37 models with information of precipitation predictions under the $SSP_5 - 8._5$ scenario or fossil-fueled economy.

6. Concluding Remarks

It is increasingly clear that climate change, through a series of microeconomic and macroeconomic channels, can impact individual financial institutions and the financial system. Nevertheless, quantifying this impact poses significant challenges. One of the tools to measure the effect of climate risks on the financial system —that has gained prominence among financial authorities around the world— are climate risk stress tests. These exercises aim to assess the resilience of the financial system under climate trajectories which capture different socioeconomic paths that reflect the combination of physical and transition risks.

We develop the first climate risk stress-test for the Peruvian financial system following a top-down approach. Focusing on the microeconomic channel, we evaluate how heavy rainfall and droughts under a scenario of pure physical risk will marginally affect the probability of default (PD) of debtors on a 30-year horizon (2050). Using information of the Credit Bureau Data Report, the National Oceanic and Atmospheric Administration (NOAA — PERSIANN-CCS-CDR) and the CMIP6 precipitation predictions (37 modelling groups), we calibrate the marginal impacts differentiating by economic sector and geographical location (district level). We find that, on average, by December 2050, the probability of default of the Peruvian financial system as a whole would increase by 4.9% on average with respect to December 2020. Particularly, the PD of the debtors located in the northern coast (Piura, Lambayeque) and the southern highlands (Ayacucho, Cusco) of Peru would be negatively affected by heavy rainfall, while the PD of rainforest regions (Madre de Dios, Ucayali) would be negatively affected by droughts. The economic sectors significantly affected by those chronic and acute risks will be agriculture, commerce, and transportation & communications.

However, this climate risk stress test could be enhanced to better capture the potential impact of climate change on the financial system in different aspects. First, the marginal impact of extreme precipitation events on default probabilities (PD), could be complemented with the assessment of the marginal effect on loss given default (LGD)[19]. Second, in addition to precipitations, other climate variables could be included in the climate risk stress test. For example, changes in sea surface temperature (SST) can negatively affect the fishing industry and, thus, the financial institutions exposed to that sector.

Third, the marginal impact of these physical risk events on macroeconomic conditions could be studied in addition to their impact on financial institutions' counterparties. These macroeconomic shocks —such as lower economic growth and labor productivity— would also affect financial institutions due to a second-round effect on the payment capacity of debtors, increasing credit risk. Fourth, climate risk may affect other traditional risk categories, such as market risk, liquidity risk and operational risk. Nevertheless, quantifying the impact on these risk categories will be considerably more challenging due to data limitations. Finally, a more complete climate risk stress test should also consider scenarios with different socioeconomic pathways that reflect less physical risks and more transition risks, like the $SSP_{1-1.9}$ "taking the green road" scenario.

[19] In particular, floods caused by heavy rainfall could damage property and assets posted as collateral, increasing the LGD.

Appendix

Appendix 1

SSP Baseline Scenarios - Average annual GDP growth pathways used by IAM under CMIP6: World, LAC, Peru

GDP	SSP1		SSP2		SSP3		SSP4		SSP5	
	2020-2050	2050-2100	2020-2050	2050-2100	2020-2050	2050-2100	2020-2050	2050-2100	2020-2050	2050-2100
World	3.6%	1.3%	2.8%	1.7%	1.9%	0.9%	2.7%	1.0%	4.3%	2.1%
LAC	3.4%	1.3%	2.7%	1.7%	2.1%	1.2%	2.5%	1.2%	4.0%	1.8%
Peru	3.9%	1.0%	3.3%	1.5%	2.7%	1.4%	3.1%	1.1%	4.3%	1.3%

Source: International Institute for Applied Systems Analysis - SSP Public Database.

Appendix 2

Precipitation Modelling Center of CMIP6 used in the climate risk stress test

Model Name	Modelling Centre
ACCESS-CM2 (published in 2019)	CSIRO-ARCCSS (Commonwealth Scientific and Industrial Research Organisation, Australian Research Council Centre of Excellence for Climate System Science)
AWI-CM-1-1-MR (published in 2018)	AWI (Alfred Wegener Institute)
BCC-CSM2-MR (published in 2017)	BCC (Beijing Climate Center)
CAMS-CSM1-0 (published in 2016)	CAMS (Chinese Academy of Meteorological Sciences)
CanESM5 (published in 2019)	CCCMA (Canadian Centre for Climate Modelling and Analysis)
CanESM5-CanOE (published in 2019)	CCCMA (Canadian Centre for Climate Modelling and Analysis)
CESM2	NCAR (National Center for Atmospheric Research)
CESM2-WACCM (published in 2018)	NCAR (National Center for Atmospheric Research)

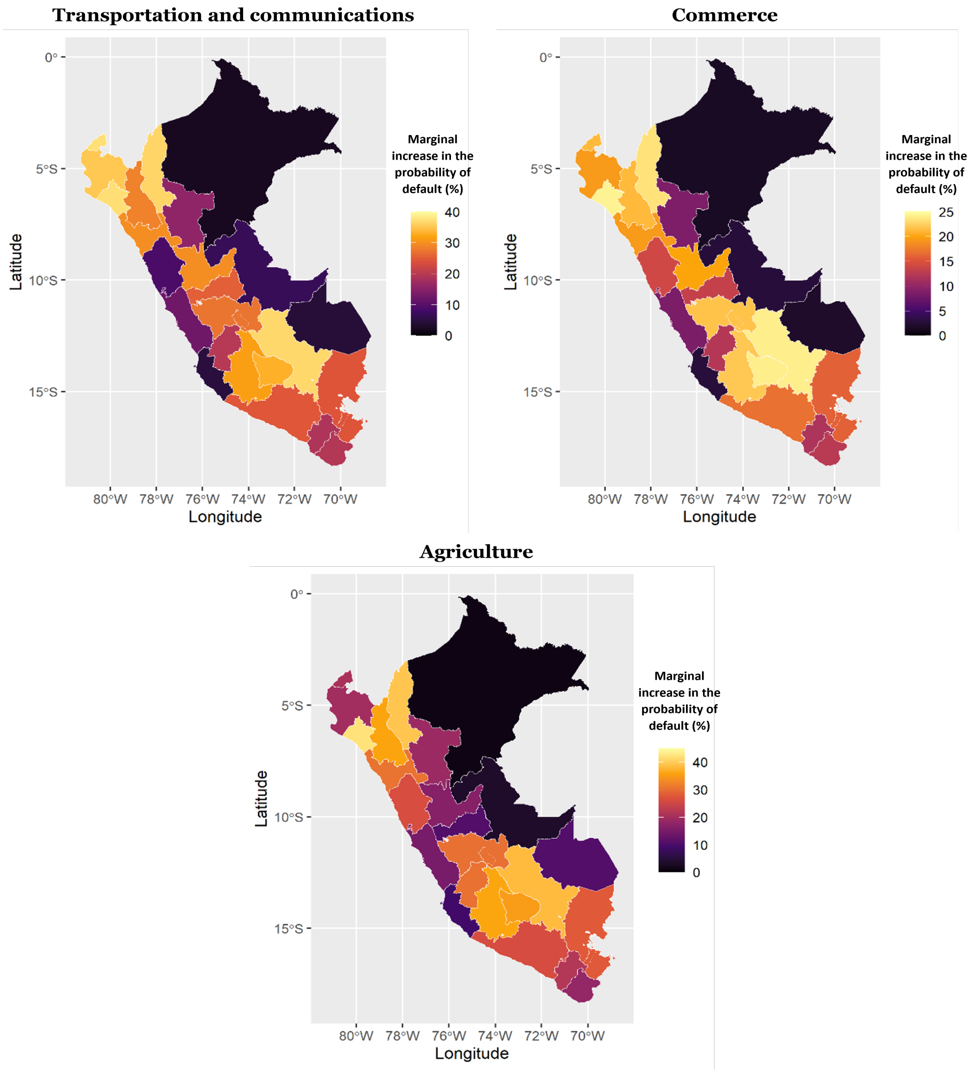
CMCC-CM2-SR5 (published in 2016)	CMCC (Centro Euro-Mediterraneo per I Cambiamenti Climatici)
CMCC-ESM2 (published in 2021)	CMCC (Centro Euro-Mediterraneo per I Cambiamenti Climatici)
CNRM-CM6-1 (published in 2017)	CNRM-CERFACS (National Center for Meteorological Research, Météo-France and CNRS laboratory, Climate Modeling and Global change)
CNRM-CM6-1-HR (published in 2017)	CNRM-CERFACS (National Center for Meteorological Research, Météo-France and CNRS laboratory, Climate Modeling and Global change)
CNRM-ESM2-1 (published in 2017)	CNRM-CERFACS (National Center for Meteorological Research, Météo-France and CNRS laboratory, Climate Modeling and Global change)
E3SM-1-1 (published in 2019)	E3SM-Project RUBISCO (Energy Exascale Earth System Model, Reducing Uncertainty in Biogeochemical Interactions through Synthesis and COmputation)
EC-Earth3-CC (published in 2021)	EC-Earth-Consortium
EC-Earth3-Veg-LR (published in 2019)	EC-Earth-Consortium
FGOALS-f3-L (published in 2017)	CAS (Chinese Academy of Sciences)
FGOALS-g3 (published in 2017)	CAS (Chinese Academy of Sciences)
FIO-ESM-2-0 (published in 2018)	FIO-QLNM (First Institute of Oceanography (FIO) and Qingdao National Laboratory for Marine Science and Technology (QNLM))
GFDL-ESM4 (published in 2018)	NOAA-GFDL (National Oceanic and Atmospheric Administration, Geophysical Fluid Dynamics Laboratory)
HadGEM3-GC31-LL (published in 2016)	MOHC NERC (Met Office Hadley Centre, Natural Environmental Research Council)
HadGEM3-GC31-MM (published in 2016)	MOHC (Met Office Hadley Centre)
IITM-ESM (published in 2015)	CCCR-IITM (Centre for Climate Change Research, Indian Institute of Tropical Meteorology)
INM-CM4-8 (published in 2016)	INM (Institute of Numerical Mathematics)
INM-CM5-0 (published in 2016)	INM (Institute of Numerical Mathematics)

IPSL-CM6A-LR (published in 2017)	IPSL (Institut Pierre-Simon Laplace)
KACE-1-0-G (published in 2018)	NIMS-KMA (National Institute of Meteorological Sciences/Korea Met. Administration)
MCM-UA-1-0 (published in 1991)	UA (University of Arizona - Department of Geosciences)
MIROC6 (published in 2017)	MIROC (Atmosphere and Ocean Research Institute (AORI), Centre for Climate System Research - National Institute for Environmental Studies (CCSR-NIES) and Atmosphere and Ocean Research Institute (AORI))
MIROC-ES2L (published in 2018)	MIROC (Atmosphere and Ocean Research Institute (AORI), Centre for Climate System Research - National Institute for Environmental Studies (CCSR-NIES) and Atmosphere and Ocean Research Institute (AORI))
MPI-ESM1-2-LR (published in 2017)	MPI-M AWI (Max Planck Institute for Meteorology (MPI-M), AWI (Alfred Wegener Institute))
MRI-ESM2-0 (published in 2017)	MRI (Meteorological Research Institute, Japan)
NESM3 (published in 2016)	NUIST (Nanjing University of Information Science and Technology)
NorESM2-LM (published in 2017)	NCC (Norwegian Climate Centre)
NorESM2-MM (published in 2017)	NCC (Norwegian Climate Centre)
TaiESM1 (published in 2018)	AS-RCEC (Research Center for Environmental Changes)
UKESM1-0-LL (published in 2018)	MOHC, NERC, NIMS-KMA, NIWA (Met Office Hadley Centre, Natural Environmental Research Council, National Institute of Meteorological Science / Korean Meteorological Administration (NIMS-KMA), National Institute of Weather and Atmospheric Research (NIWA))

Source: CMIP6 (https://confluence.ecmwf.int/display/CKB/CMIP6%3A+Global+climate+projectionsCMIP6:Globalclimateprojections-Models).

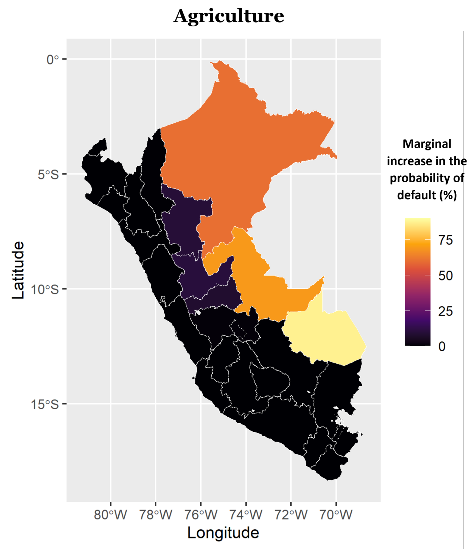
Appendix 3

(a) Marginal impact of heavy rainfall on the probability of default of the Financial System by region and economic activity (%)



Source: Credit Bureau Data Report, NOAA, CMIP6, Ministerio de Ambiente.
Average impact of 37 models with information of precipitation projections under the $SSP_5 - 8._5$ scenario or fossil-fueled economy.

(b) Marginal impact of droughts on the probability of default of the Financial System by region and economic activity (%)



Source: Credit Bureau Data Report, NOAA, CMIP6, Ministerio de Ambiente.
Average impact of 37 models with information of precipitation projections under the $SSP_5 - 8._5$ scenario or fossil-fueled economy.

References

Alogoskoufis, S., Dunz, N., Emambakhsh, T., Hennig, T., Kaijser, M., Kouratzoglou, C., and Salleo, C. (2021). ECB economy-wide climate stress test *Occasional Paper*, (2021/281).

Ara Begum, R., Lempert, R., Elham, A., Benjaminsen, T. A., Bernauer, T., Cramer, W., Cui, X., Mach, K., Nagy, G., Stenseth, N. C., et al. (2022). Point of departure and key concepts.

Bank of England. (2021). GGuidance for participants of the 2021 Biennial Exploratory Scenario: Financial risks from climate change.

Bank of England. (2022). *Results of the 2021 Climate Biennial Exploratory Scenario (CBES).* https://www.bankofengland.co.uk/stress-testing/2022/results-of-the-2021-climate-biennial-exploratory-scenario. Obtenido de Bank of England.

Basel Committee on Banking Supervision, B. C. (2020). Climate-related financial risks: A survey on current initiatives.

Basel Committee on Banking Supervision, B. C. (2021). Climate-related risk drivers and their transmission channels. *Bank for International Settlements.*

Baudino, P., Goetschmann, R., Henry, J., Taniguchi, K., and Zhu, W. (2018). *Stress-testing banks: a comparative analysis.* Bank for International Settlements, Financial Stability Institute.

Espinosa-Tasón, J., Berbel, J., Gutiérrez-Martín, C., and Musolino, D. A. (2022). Socioeconomic impact of 2005–2008 drought in Andalusian agriculture. *Science of The Total Environment.*

European Central Bank - Banking Supervision. (2021). Climate risk stress test - SSM stress test 2022.

European Central Bank - Banking Supervision. (2022a). 2022 climate risk stress test.

European Central Bank - Banking Supervision. (2022b). Macro-financial scenarios for the 2022 climate risk stress test.

Government of Canada, G. (2021). *Forcing scenarios.* https://climate-scenarios.canada.ca/?page=forcing-scenarios. Obtenido de Canadian Climate Data and Scenarios.

Government of Canada, G. (2022). *CMIP6 and shared socio-economic pathways overview.* https://climate-scenarios.canada.ca/?page=cmip6-overview-notes. Obtenido de Canadian Climate Data and Scenarios.

Gutiérrez, B., Salinas, J. C., and Wong, S. (2019). Agricultural credits and climate events: Measuring the impacts of heavy rains on the financial situation of Peruvian farmers. *Documento de Trabajo SBS.*

Haddad, E. A. and Teixeira, E. (2015). Economic impacts of natural disasters in megacities: The case of floods in São Paulo, Brazil. *Habitat International*, 45:106–113.

Hare, B., Brecha, R., and Schaeffer, M. (2018). Integrated assessment models: what are they and how do they arrive at their conclusions? *Climate Analytics.*

Inoue, H. (2021). The Economic Impact of Heavy Rains on Supply Chains. *Available at SSRN 3875196.*

Monasterolo, I., Nieto, M., and Schets, E. (2022). The good, the bad and the hot house world:

conceptual underpinnings of the NGFS scenarios and suggestions for improvement. *SSRN.*

Network for Greening the Financial System. (2020). NGFS climate scenarios for central banks and supervisors.

Network for Greening the Financial System. (2021). Climate Scenarios Database - Technical Documentation V2.2.

Network for Greening the Financial System. (2021). Scenarios in Action: A progress report on global supervisory and central bank climate scenario exercises. *NGFS Publications.*

Network for Greening the Financial System. (2022). *Origin and Purpose.* `https://www.ngfs.net/en/about-us/governance/origin-and-purpose`. Obtenido de Network for Greening the Financial System.

O'Neill, B. C., Tebaldi, C., Van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J., et al. (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. *Geoscientific Model Development*, 9(9):3461–3482.

Rentschler, J., Kim, E., Thies, S., De Vries Robbe, S., Erman, A., and Hallegatte, S. (2021). Floods and Their Impacts on Firms: Evidence from Tanzania. *The World Bank.*

Sadeghi, M., Nguyen, P., Naeini, M. R., Hsu, K., Braithwaite, D., and Sorooshian, S. (2021). PERSIANN-CCS-CDR, a 3-hourly 0.04° global precipitation climate data record for heavy precipitation studies. *Scientific Data*, 1-11.

SENAMHI (2020). *Mapa Climático del Perú.* `https://www.senamhi.gob.pe/?p=mapa-climatico-del-peru`. Obtenido de Servicio Nacional de Meteorología e Hidrología del Perú.

Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S., and Hsu, K.-L. (2018). A Review of Global Precipitation Data Sets: Data Sources, Estimation, and Intercomparisons. *Reviews of Geophysics*, 56(1):79–107.

Taylor, K., Stouffer, R., and Meehl, G. (2012). An Overview of CMIP5 and the Experiment Design. *Bulletin of the American meteorological Society*, 485-498.